An Analytical Model for Predicting the Impact of Maintenance Resource Allocation on National Airspace System Availability

By

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ABSTRACT

This paper presents an analytical model and software tool that can be used by non-experts to relate FAA maintenance resources including staffing, training, shift allocation, and geographical deployment to NAS facility and service downtime and availability. The analytical methodology and tool presented in this paper make it possible for any user to rapidly assess how changes in staffing, training, equipment count, and reliability will impact outage time, availability, maintenance backlog and technician utilization. It allows users to easily perform parametric studies on a variety of "what if" scenarios related to economics and capacity. The most significant benefit is that these results cam now be made available to analysts and decision makers. The net result will be more informed decisions that to account for the impact of maintenance resources on NAS capacity and overall economics.

INTRODUCTION

The number and complexity of the facilities that the Federal Aviation Administration Airway Facilities (AF) organization must support is growing. As a result, methods and tools are needed to assess the impact of resource allocation decisions on downtime, technician utilization, maintenance backlog, and equipment availability. This paper presents a model to predict such quantities for the 9 regions that make up the National Airspace System (NAS). The inputs to the model include the number and location of personnel, how maintenance personnel are scheduled, and the breadth of their qualifications. The model can be used to assess the impact of various "what if" scenarios such as

- increasing training to fix more types of equipment
- enlarging maintenance sectors (i.e., increased numbers of technicians on watch vs. the longer travel times inherent in larger sectors)
- replacing older equipment with lower reliability and the resulting impact on technician utilization and overall system availability.
- geographical deployment of technicians to increase or decrease travel time

The primary innovation in the work presented in this paper is that it based on *analytical* models rather than discrete event simulations. Analytical models can be solved much more rapidly than simulations and provide exact results. Thus, analytical models facilitate rapid parametric studies. This capability is important in high level administrative and planning activities because answers are often needed quickly in response to circumstances that can not always be predicted. The next section of this paper provides a description of the analytical model. This is followed by a description of a tool implementing the model and validation by comparison with both empirical results and discrete event simulations. Finally, we will present uses of the tool in the management of maintenance resources within the Airways Facilities (AF) organization of the FAA.

MODEL DESCRIPTION

The objective of the maintenance model is to estimate the outage time as a function of the number of qualified technicians on watch and the number of facilities in the SSC that these technicians must support. The key to performing this estimate is the analytical results derived from queuing theory, and in particular, finite queuing equations.

The basis of this model is an analytical finite queuing model based on the following assumptions:

1. Technicians and facilities are organized into Sector Service Centers (SSCs), each with a defined number of facilities and technicians

2. Operating time is continuous, and staffing is maintained at a uniform level.

3. All facilities in the cost center have the same failure rate and repair rate[1].

4. Failures occur independently.

5. Only one technician is dispatched to service each repair.

6. All qualified technicians are equally proficient at making the repair. However, only qualified technicians are dispatched

7. Facility failure rates and repair times are exponentially distributed

Under these assumptions, the probability of an empty queue is given by [2]

$$p_o := \left[\sum_{i=0}^{c-} \frac{n!}{i!\,(n-i)!} \cdot \left(\frac{\lambda}{\mu}\right)^i + \frac{1}{c!} \sum_{i=c}^{n} \frac{n!}{(n-i)!} \, \frac{1}{c^{(i-c)} \cdot c!} \cdot \left(\frac{\lambda}{\mu}\right)^i \right]^{-1} \qquad \text{Equation 1}$$

Where

p_o	is the Probability of empty queue (technician being available)
c	is the average staffing level (number of qualified technicians) for each SSC
n	is the number of facilities in each cost center
λ	is the model failure rate
μ	is the model repair time

The expected number of facilities with failures in each queue is given by

$$L = p_o \cdot \left[\sum_{i=0}^{c-1} (c-i) \cdot \frac{n!}{i!(n-i)!} \cdot \left(\frac{\lambda}{\mu}\right)^i + \frac{1}{c!} \cdot \left[\sum_{i=0}^{c-1} i \cdot \frac{n!}{i!(n-i)!} \cdot \frac{1}{c^{i-c}} \left(\frac{\lambda}{\mu}\right)^i \right] \right]$$

Equation 2

where L is the expected number of facilities with failures (also referred to as the queue length).

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[1] This is a necessary approximation for the analytical approach. Heterogeneous failure rates and repair rates require the use of a discrete event simulation. However, in most cases, the results of discrete event simulation and the equivalent analytical treatment using weighted averages do not differ for the range of parameters used in this analysis.

The number of facilities that are waiting and have not yet been repaired (Lq) is given by [2]

$$L_q = L - c + p_o \cdot \left[\sum_{i=0}^{c-1} (c-i) \cdot \frac{n!}{i!(n-1)!} \cdot \left(\frac{\lambda}{\mu}\right)^i \right] \qquad \text{Equation 3}$$

Total failure duration time (W, i.e., waiting to be repaired and actually under repair) is given by

$$W = \frac{L}{\lambda \cdot (n-L)} \qquad \text{Equation 4}$$

The time waiting for the start of repairs is given by

$$W_q = \frac{L_q}{\lambda \cdot (n-L)} \qquad \text{Equation 5}$$

The innovations in this approach are on in how the number of technicians is determined, the estimation of the service time, μ, and the calculation of technician utilization. These topics are discussed in the following section.

Number of Qualified Technicians

The number of technicians available to fix a repair, c, in equations 1 through 3, is the average number of technicians per SSC, scaled for continuous availability and qualifications, that is

$$c = \frac{N_{region} \cdot Qualfactor_{region}}{N_{SSCregion} \cdot Sfactor_{region}} \qquad \text{Equation 6}$$

Where

$N_{regiontech}$ is the number of technicians in the regions
$N_{SSC\ region}$ is the number of SSCs in the region.
$Qualfactor_{region}$ is the average proportion of facilities in the SSC that technicians in the region are capable of servicing, and
$Sfactor_{region}$ is the staffing factor, i.e, the number of full time equivalents needed to create a continuous (7 days per week, 24 hours per day) watch position.

This equation can be understood as follows: $N_{regiontech}/N_{SSCregion}$ is the average number of technicians per SSC (in the region). The average number on watch at any given time would be the average number of technicians per SSC divided by the number of technicians needed to make up a continuous watch-standing schedule. Finally, the average technician can only fix a certain proportion of facilities in the region, i.e., the term $Qualfactor_{region}$.

The parameter $Qualfactor_{region}$ is defined by

Equation 7

$$\text{Qualfactor}_{\text{region}} = \frac{\text{Qual}_{\text{region}}}{\text{N}_{\text{Region,uniqueFaccodes}}}$$

Where

$N_{\text{region uniqueFacodes}}$ is the number of unique facility types in the average SSC for the region and $\text{Qual}_{\text{region, avg}}$ is the average number of facility types for which each technician is qualified

In other words, Qualfactor is the average proportion of facilities within the SSC that can be fixed by the average technician. The number of unique facilities can be derived from FAA databases on equipment inventory referred to the as the Facility Master File or Facility (FMF) or Services, and Equipment Profile (FSEP) [5]. The number of average facilities for which technicians are qualified can be derived from the average number of courses taken by each technician, the number of courses required for qualification on a given and FAA training data.

The quantity Sfactor is currently set at 5 (i.e., 5 full time equivalents are needed to staff one watch continuously) for all regions.

Number of Facilities

The number of facilities n, in an SSC is defined by

$$n = \frac{N_{\text{facilities region}}}{N_{\text{SSCregion}}} \qquad \text{Equation 8}$$

where $N_{\text{facilities region}}$ is the number of commissioned *facilities* reported in the Historical Population Database (HPOP) National Airspace System Performance Analysis System (NASPAS) [6] and $N_{\text{SSCregion}}$ was defined in Equation 6.

Maintenance Action Rates and MTBOs

In order to properly assess technician utilization and waiting time and their impact upon availability, it is necessary to distinguish among multiple types of *maintenance actions.* A maintenance action requires that a technician be dispatched to work at a facility. However, *not all maintenance actions result in outages.* This is particularly true for FAA facilities in which there is redundancy. Thus, a repair technician may be dispatched to repair or maintain a failed channel, but the facility as a whole may still be available (i.e., providing service) through the backup channel. In the case of an *outage,* the facility is no longer providing service, either because the failure affected both the primary and backup channels or because a second failure occurred prior to the first being fixed. It is important to note that technicians are occupied for all *maintenance actions,* but availability is affected only by actual facility outage as been reported in the official FAA outage reporting system called the National Airspace Performance Reporting System (NAPRS) [3]. In general, the relationship between the service rate λ and the Mean Time Between Outages (MTBO) is defined by

$$\lambda = \frac{1/R}{\text{MTBO}} \qquad \text{Equation 9}$$

Where

R	is the outage to failure ratio, and
MTBO	is the mean time between outages

Given the MTBO and the value of R, it is possible to calculate a service rate. In order to maintain close consistency with existing FAA outage reporting, we have derived MTBO from NASPAS data. However, an adjustment is required because of a difference in the way FAA facilities are counted in the FSEP vs. the manner in which MTBO is calculated in NASPAS. The difference is due to the fact that radio communication air to ground links have multiple frequncies in place, i.e., transceivers at each facility, each set at a different frequency. Values for the MTBO were based on regional averages taken from NASPAS and adjusted for the frequencies in place (as reported in NASPAS) vs. the actual number of facilities (as reported in the FSEP). Thus,

$$MTBO_{region} = MTBO_{region.NASPAS} \cdot \frac{HPOP_{region}}{HPOP_{Freqs.region}}$$

Equation 10

where

$MTBO_{region}$	is the adjusted mean time between outages
$MTBO_{region.NASPAS}$	is the NASPAS reported MTBO for the region
$HPOP_{region}$	is the number of facilities in the region derived from the HPOP database
$HPOP_{freqs.region}$	is the number of facilities and frequencies reported in the HPOP database

As will be described below, outage time is largely determined by whether an outage is scheduled or unscheduled. Thus a key parameter is the ratio of scheduled to unscheduled outages for each region which is determined by

$$x_{region} = \frac{N_{outages,unsched,region}}{N_{outages,region}}$$

Equation 11

Where

x_{region}	is the proportion of unscheduled outages in the region
$N_{outages.unsched.region}$	is the number of unscheduled outages in the region and
$N_{outages..region}$	is the total number of outages in the region

It is assumed that the *maintenance action* rate is directly proportional to the *outage rate* (the reciprocal of the MTBO) for both scheduled and unscheduled failures. Thus, the unscheduled maintenance action rate is then given by

$$\lambda_{unsched,\ region} = x_{region}\,\lambda_{tot,\ region}$$

Equation 12

Where

$\lambda_{unsched,\ region}$ is the unscheduled maintenance action rate (for any aggregation including the region) and

$\lambda_{tot,\ region}$ is the total maintenance action rate of the region

Similarly, for scheduled outages

$$\lambda_{sched\cdot region} = (1 - x_{region})\lambda_{tot,\ region}$$

Equation 13

Where

$\lambda_{sched.region}$ is the scheduled maintenance action rate for the region.

Repair Times and Repair Rates

A key concept in this model is the need to distinguish between an *outage time* and a *repair time*. The repair time is the time needed to perform the repair. The outage time includes the repair time and additional times that will be discussed below. The Official FAA NAPRS data reports outage time, *not* repair times.

In order to derive the repair time from the outage time, we observe that most outages are repaired almost immediately. However, longer duration outages are nearly always a combination of repair time and waiting time. Thus, a methodology that defensibly incorporates only shorter duration outages can be used to define a fairly reasonable estimate of the repair time.

We have derived such a methodology using the exponential distribution for repair times. The analytical queuing equations as well as most analytical treatments of reliability and availability [7] assume an exponential distribution for repair rate μ, i.e.,

$$N_{repair}(t) = N_{tot}\,\mu e^{-\mu t}$$

Equation 14

where $N_{repair}(t)$ is the number of facilities having a repair time of t (actually, in the interval between t and t+dt) and N_{tot} is the total number of facilities that have failed and are being repaired. Taking the logarithm of the above equation results in the following expression

$$\ln[N_{repair}(t)] = -\mu t + \ln[\mu N_{tot}]$$

Equation 15

This equation was an excellent fit to the NAPRS outage data (with a correlation coefficient of 0.992) for repair times of less than 10 hours [1]. An example of the close fit can be seen in Figure 1, which shows the projected vs. actual number of repair times for 120,000 outages from NAPRS data reported in 1995.

There is a reciprocal relationship between the average repair rate and the average repair time, or i.e.,

$$MTTR = 1/\mu$$

Equation 16

where MTTR is the mean time to repair, the commonly used terminology of the average repair time.

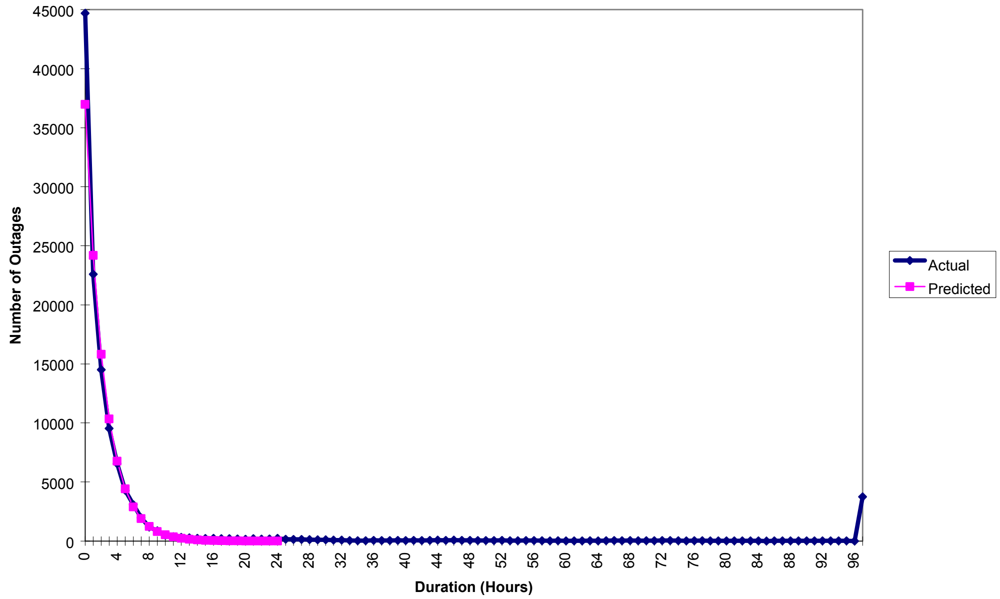

Figure 1 Actual and Predicted Frequency Distribution of all NAPRS reportable outage times from 1995 data. Unscheduled outage times are net of travel.

Outage Times and Availability

Outage times are dependent on whether the maintenance action is scheduled or unscheduled, and whether the repair action involves an outage at all. Table 1 shows the general relationship.

Table 1. Relationship between outage times and repair action type

Maintenance Action Type	Scheduled/Unscheduled	Outage Time
Outage	Scheduled	Repair Time
	Unscheduled	Repair time, waiting time, one-way travel time, and time waiting for start of shift (if qualified technicians not continuously available)
Maintenance Action (not an outage)	Scheduled	None
	Unscheduled	None

As is evident from table 1, only *unscheduled outage times* are affected by maintenance staffing resources.

When one or more qualified technicians is on watch, then the equations defined in section 2.1 for waiting time correctly predict the waiting time. However, if a qualified technician is not on watch continuously, then there will be some periods during which an unscheduled repair will wait. This wait will include (a) the wait for the qualified technician if he or she is busy performing another repair, and (b) the beginning of the shift of the qualified technician (if such a technician is not currently on watch).

In order to estimate unscheduled outage time, the following relations were used

$$t_{unsched} = \begin{cases} W_q + t_{travel1way} + MTTR & c \geq 1 \\ W_q + t_{travel1way} + MTTR + (1-c) \cdot t_{cycle}/2 & c < 1 \end{cases} \qquad \text{Equation 17}$$

Where

$t_{unsched}$ is the unscheduled outage time
$t_{travel1way}$ is the average 1-way travel time for the region
t_{cycle} is the cycle time for the start of the shift cycle (typically 24 hours)

For continuously staffed maintenance positions (i.e., $c \leq 1$, the first line on the Right Hand Side of Equation 17), the total unscheduled outage time is the sum of the following: the unscheduled outage time is the time due to waiting for the technician (W_q from Equation 4), the 1-way travel time, and the actual mean time to repair.

For non-continuously staffed maintenance positions (the second line of the Right Hand Side of Equation 17), the unscheduled outage time includes the terms for continuously staffed positions plus an additional time related to the cycle time. This final term can be understood as follows. If a technician came for a very short time each shift cycle, then the average time that each repair would have to wait would be half the cycle time. As c increases (i.e., more technician time is available for each watch), then the waiting time due to a technician to return to the watch decreases. Finally, when the watch standing for a qualified technician becomes continuous, $t_{unsched}$ no longer includes a term for the absence of a qualified technician.

The average outage time accounting for both scheduled and unscheduled outages is the weighted average of the unscheduled outage time (equation 17) and the scheduled outage time, which is simply the repair time (from table 1), i.e.,

Equation 18

$$MOT := (1-x) \cdot MTTR + x \cdot t_{unsched}$$

Where

MOT is the mean outage time
x is the unscheduled outage ratio for the SSC (or other unit under consideration)
μ is the average repair rate (the reciprocal of the average repair time)

Given the relationship for mean outage time shown in Equation 18, it is possible to define the availability of the SSC as

$$A_{MR} := \frac{MTBO}{MTBO + MOT} \qquad \text{Equation 19}$$

Where

A_{MR} is availability attributable to maintenance resource
MTBO is the mean time between outages as derived from NASPAS (see above)

The availability of any facility also must account for long term outages due to capital improvements or other administrative reasons. This is accounted for by considering the unavailability of the facility due to these causes and subtracting that availability from the availability shown in Equation 19. That is,

$$A_{obs} = A_{MR} - U_{LT} \qquad \text{Equation 20}$$

where

A_{obs} is the observed facility availability as reported in NAPRS

A_{MR} is the maintenance resource affected portion of availability (from Equation 19)

U_{LT} is the long-term unavailability of equipment due such factors as administrative outages, the time awaiting capital improvements, decisions to temporarily shut down a facility, etc. This term includes factors not related to maintenance resource allocation.

It should be noted that both A and U are numbers between 0 and 1.

Technician Utilization

Technician utilization is defined by the standard queuing equations when at least one technician is standing watch, but must be modified to account for technician absence when c is less than unity as shown in the following equation when c is less than 1

$$U := \begin{cases} U_o + (1-c)\cdot\lambda\cdot t_{cycle}\cdot\dfrac{MTTR+(2-x)\cdot t_{travel1way}}{c} & c \le 1 \\ U_o & c > 1 \end{cases}$$

where U_o is the steady state utilization for a finitie queue, i.e., [2]

$$U_o = 1 - p_o \cdot \left[\sum_{i=0}^{c-1} \frac{c-i}{c} \cdot \frac{n!}{i!(n-i)!} \cdot \left(\frac{\lambda}{\mu}\right)^i \right] \qquad \text{Equation 22}$$

For non-continuously staffed maintenance positions (the first line of the Right Hand Side of Equation 21), the first term represents the utilization for all technicians on watch. The second represents the utilization accounting for the fact that a qualified technician is not always present. Within this term, the part before the fraction represents the number of facilities that fail while the technician is absent, and the second represents the amount of time that the technicain can be at the facility. However, for continuously staffed maintenance positions (i.e., $c \le 1$, the second line on the Right Hand Side of Equation 21), the utilization is simply the finite queuing model utilization as shown in Equation 22. Thus, when c is greater than 1, then the average technician utilization is constant.

A SOFTWARE TOOL FOR IMPLEMENTING THE MODEL

The model developed above has been implemented in a tool called SMART 4 (System Maintenance Allocation of Resources Tool). SMART 4 predicts

- facility availability,
- technician utilization,
- outage time,
- waiting time,
- number of backlogged tasks.

as a function of staffing, training, number of facilities, travel time, average facility outage time, and average facility MTBO. Analyses are performed on a representative sector defined by equipment with the averages of these values for each FAA region.

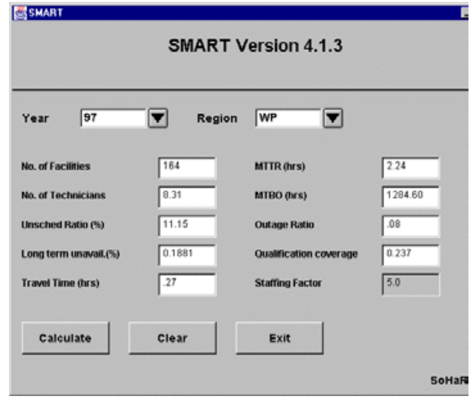

Figure 2. SMART initial facility input screen

To perform an analysis, the user selects a region to be modeled and the year. SMART 4 retrieves parameters on staffing, MTBO, MTTR, number of facilities, outage ratio, and ratio of scheduled to unscheduled outages from its database. The calculations are then performed in accordance with the equations defined in the previous section and results presented as shown in Figure 3.

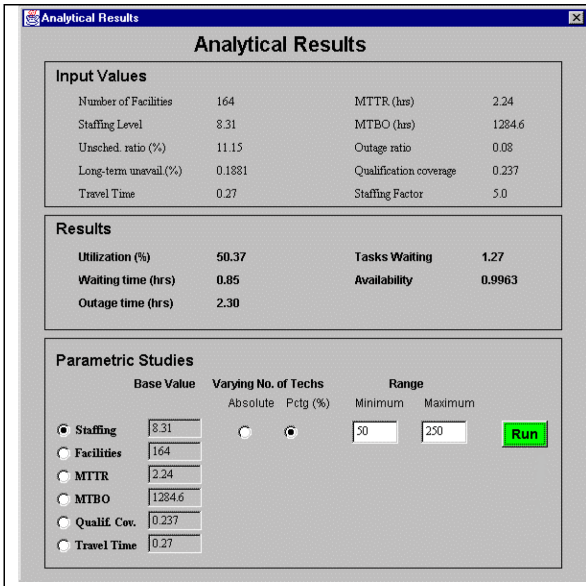

Figure 3. SMART 4 Results and Parametric Analysis Screen

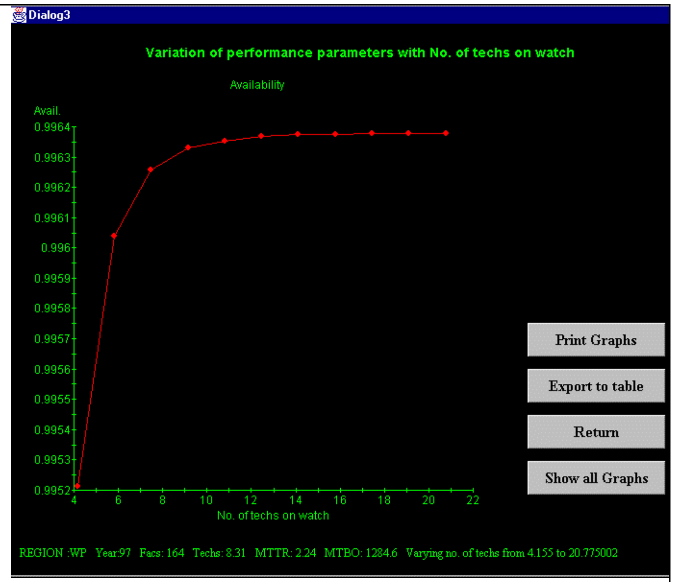

Figure 4. SMART 4 parametric analysis showing Impact of Technician Staffing On Availability

The bottom panel in Figure 3 shows the input to set up a parametric analysis for varying staffing between 50% and 250% of the current value. The results are displayed in Figure 4. The results show availability varying from 0.9952 to 0.9964. However, at the current technician staffing level (8.31 technicians per shift on the average), there is little benefit to be gained by increasing staffing. On the other hand significantly reducing staffing from these levels will result in a disproportionate degradation of availability (or increase in downtime).

Figure 4 demonstrates the primary benefit of the analytical model. Parameters can be changed easily, and results presented instantly. This time is in contrast to the the results of a discrete event simulation for an equivalent which can take several minutes to generate. The speed at which results can be calculated with an analytical method facilitates the performance of multiple "what if" scenarios. The following input parameters can be changed:

- Staffing

- Number of Facilities
- Repair Time (MTTR)
- Reliability (MTBO)
- Training (measured as qualification coverage, the proportion of facilities for which the average technician on watch is qualified), and
- Travel time

Any of these parameters can be varied either in absolute or relative (percent change) terms.

VALIDATION

Validation of the results of this model consisted of demonstrating that

a. Agreement between FAA reported availability and model predictions

b. Agreement betweenThe results of the analytical model are close to the results of a Discrete Event Simulator for the same cases.

The results of these validations are presented below.

Comparison of Model Results with Availability Derived FAA NASPAS Data

There was good agreement between the availability predictions from the analytical model and NASPAS data. For example, for 1997data, the average error for the national availability prediction was 0.07%. Because of the close agreement between observed and predicted availability, the relative errors are better understood by examining the results for *unavailability*. Figure 5 and Table 2 show the comparison of observed (as determined by NASPAS) and predicted results for regional averages in 1997.

Fig 5 Results comparisons between Observed (NASPAS) and Predicted (using model described in previous section)

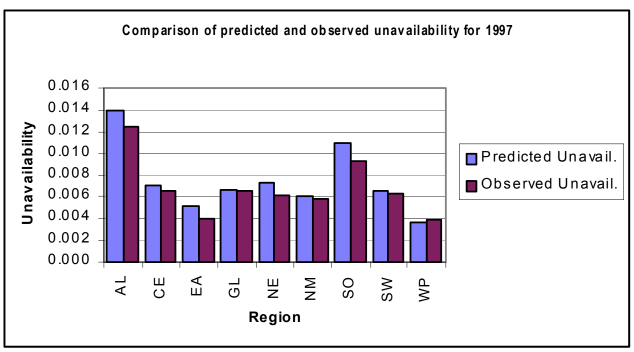

Table 2. Comparison of average observed and predicted facility unavailability

Region	Predicted Unavail.	Observed Unavail.	Relative Error (%)	Absolute Error
AL	0.0140	0.0125	12.00	0.00150
CE	0.0071	0.0066	7.58	0.00050
EA	0.0052	0.0040	30.00	0.00120
GL	0.0067	0.0066	1.52	0.00010
NE	0.0073	0.0062	17.74	0.00110
NM	0.0060	0.0058	3.45	0.00020
SO	0.0110	0.0093	18.28	0.00170
SW	0.0066	0.0063	4.76	0.00030
WP	0.0037	0.0039	5.13	-0.00020

Figure 5 graphically shows the agreement for unavailability. Table 2 shows these results in numerical form and shows that relative errors are gemerally higher when absolute results are lower. This is most evident in the case of the Eastern region, in which the observed results were 30% higher than the model results – even though the absolute error was quite low (0.0012). In general, however, the model correctly predicts the ranking of the unavailability of regions. The valid range covers regions of both relatively high unavailability (e.g., the AL region, where travel times are long and conditions cause long repair times) and low unavailability (e.g., WP and EA regions where travel times are much shorter).

Comparison with Discrete Event Simulation Results

In this section, the outputs from representative SSCs from each of the 9 FAA regions are compared using discrete event simulation whose validation was discussed in [8]. The results of both the analytical model and discrete event simulation are shown in Table 3. There is good agreement through a relatively broad range of input parameters of the representative SSCs. For example, the number of facilities varies from 38 to 152, and the MTBO ranges from 1280 to 2248 hours.

The maximum percentage difference is approximately 8% so for waiting time and queue lengths, below 2% for most of the other quantities and quite high for unavailability (18% in one case, though this is understandable because the quantities are very small)

Table 3. Comparison of results between Discrete Event Simulator and

		Inputs							Outputs					
		# facs	# techs	MTTR (hrs)	MTBO (hrs)	Outage Ratio	Long Term unavail.	QC	Wait Time (hrs)	Outage Time (hrs)	Repair Time (hrs)	Queue Length	Util. (%)	Avail.
Case 1	SMART 4.1.4	81	3	3.64	1328	0.1	0.7255	0.33	6.21	4.26	3.64	3.52	68.9	0.9882
	SMART 3.1	81	3	3.64	1328	0.1	0.7255	0.33	5.98	4.22	3.63	3.37	68.7	0.986
	% Difference								3.70	0.94	0.27	4.26	0.29	0.22
Case 2	SMART 4.1.4	38	2	2.53	2218.2	0.08	0.4999	0.5	0.83	2.59	2.53	0.17	26.6	0.9937
	SMART 3.1	38	2	2.53	2218.2	0.08	0.4999	0.5	0.778	2.58	2.52	0.163	26.3	0.9935
	% Difference								6.27	0.39	0.40	4.12	1.13	0.02
Case 3	SMART 4.1.4	210	10	2.46	1879.1	0.08	0.3777	0.1	1.12	2.54	2.46	1.53	33.58	0.9948
	SMART 3.1	210	10	2.46	1879.1	0.08	0.3777	0.1	1.03	2.53	2.45	1.4	33.45	0.9943
	% Difference								8.04	0.39	0.41	8.50	0.39	0.05
Case 4	SMART 4.1.4	96	4	2.69	2018	0.08	0.4642	0.25	1.54	2.81	2.69	0.89	39	0.9938
	SMART 3.1	96	4	2.69	2018	0.08	0.4642	0.25	1.42	2.76	2.65	0.825	38.5	0.9934
	% Difference								7.79	1.78	1.49	7.30	1.28	0.04
Case 5	SMART 4.1.4	66	3	3	2248	0.08	0.5175	0.33	1.51	3.12	3	0.54	35.8	0.9933
	SMART 3.1	66	3	3	2248	0.08	0.5175	0.33	1.45	3.09	2.98	0.525	35.88	0.9928
	% Difference								3.97	0.96	0.67	2.78	0.22	0.05
Case 6	SMART 4.1.4	75	3	2.63	1809	0.08	0.3198	0.33	1.85	2.77	2.63	0.92	44.09	0.9951
	SMART 3.1	75	3	2.63	1809	0.08	0.3198	0.33	1.7	2.74	2.6	0.86	43.73	0.9944
	% Difference								8.11	1.08	1.14	6.52	0.82	0.07
Case 7	SMART 4.1.4	180	9	2.75	1597	0.08	0.9036	0.11	1.72	2.88	2.75	2.33	41.62	0.989
	SMART 3.1	180	9	2.75	1597	0.08	0.9036	0.11	1.59	2.86	2.744	2.16	41.56	0.988
	% Difference								7.56	0.69	0.22	7.30	0.14	0.10
Case 8	SMART 4.1.4	138	6	2.59	1966	0.08	0.498	0.13	1.41	2.7	2.59	1.17	36.97	0.9935
	SMART 3.1	138	6	2.59	1966	0.08	0.498	0.13	1.27	2.69	2.58	1.08	36.8	0.993
	% Difference								9.93	0.37	0.39	7.69	0.46	0.05
Case 9	SMART 4.1.4	152	8	2.24	1284	0.08	0.1881	0.13	1.3	2.34	2.24	1.86	40.06	0.9962
	SMART 3.1	152	8	2.24	1284	0.08	0.1881	0.13	1.17	2.31	2.22	1.68	39.7	0.9956
	% Difference								10.00	1.28	0.89	9.68	0.90	0.06

APPLICATION OF THE MODEL

The model and SMART 4, the tool which implements it, provides a basis for decision making for investment analysis, economic impact studies, and capacity studies. This section discusses two senarios on investment analysis and operational impact analysis that demonstrate the applications of the methodology and SMART 4 tool.

Investment Analysis Scenario

An example of how SMART 4 can be used to support investment analysis is an assessment of the benefit of replacing older less reliable equipment with newer more reliable equipment. For example, the average MTBO for the FAA Eastern Atlantic region is 1878.14 hrs. If this parameter were increased to 2248 hours (which is the same as the Northeast Region), the SMART 4 tool will produce the results shown in Table 4

Table 4. Result of Increasing MTBO in a Representative SSC in the Eastern Atlantic Region

Parameter	Change
Availability	increased from .9948 to .9950
Technician utilization	declined from 42% to 35%.
Waiting time	reduced from 1.32 hours to 1 hour.
Average outage time	2.56 to 2.54 hours.
Number of repairs waiting	reduced from 1.45 to 0.9.

One of the non-intuitive results from this table is that althrough the waiting time decreased by 0.32 hours, the average outage time decrease by only 0.02 hours. The reason for this can be seen in Table 1. Although both unscheduled and scheduled outages and maintenance actions not resulting in outages must wait, only the waiting time of unscheduled outages causes an increase in average outage time.

If the primary objective for the capital investment is to increase availability, then the overall increase in availability (about 1.6 hours per year per facility on the average) may not warrrant the expenditure. However, as we will show below, the increased capital investment might be justified because the staffing can be reduced from an average of 9.78 to approximately 6.5 technicians while retaining the same level of availability (0.9950). In this manner, SMART 4 has transformed the problem into the classic economic tradeoff of increased capital costs vs. reduced operating cost.

Another example of investment analysis support is evaluation of alternatives. One such alternative would be to retain the current equipment to enhance diagnostics. The result of better diagnostics would be to reduce the repair time (i.e., MTTR). A second run with the SMART tool would show that a decrease of the MTTR by 20% (a factor equivalent to the change in MTBO) results in a decrease of the outage time from 2.56 to 2.10 hours. If the objective is to reduce outage time, then this investment is a better choice.

Operational Impact Analysis Scenario

In order to demonstrate the uses of SMART for analysis of the impact on operations, we will use a scenario of reducing maintenance staffing due to budgetary constraints. The parametric analysis capabilities of SMART 4 will be demonstrated in this scenario.. Figure 6 shows the results for the the representative Northeast region sector discussed above of this contemplated staffing change after having implemented the reliability increase.

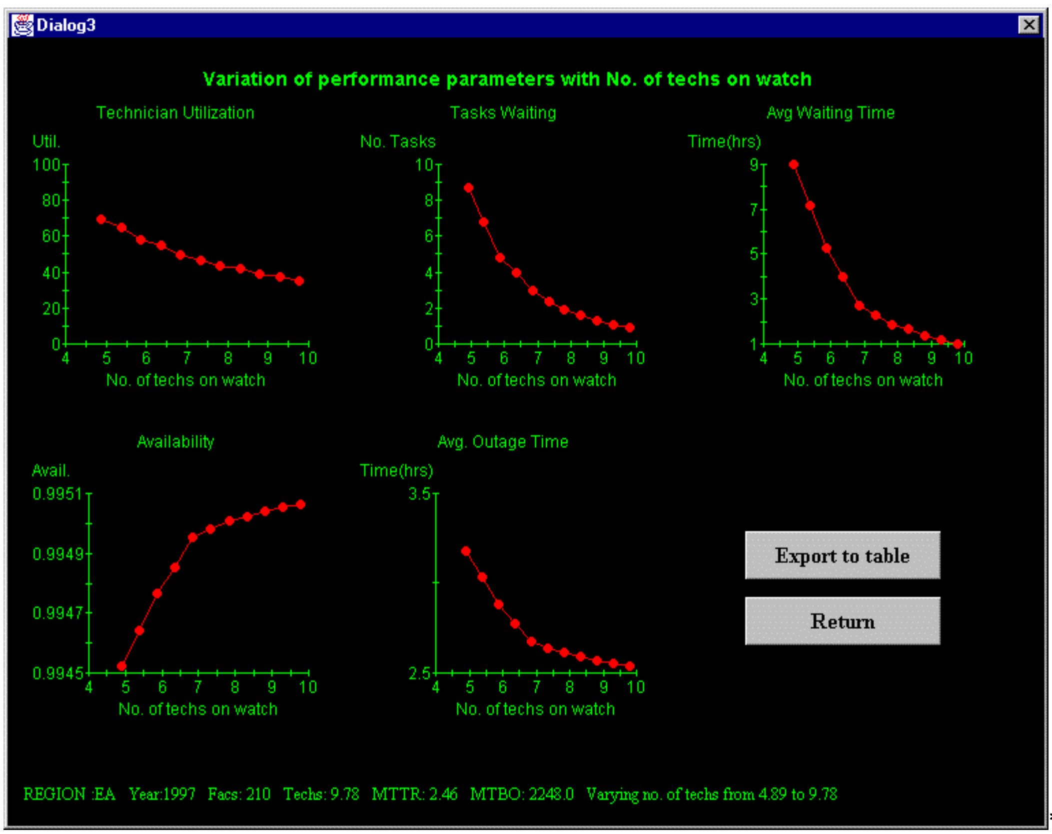

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Figure 6. Graphical view of parametric study results

The results include the following (note that the baseline is on the right of the abcissa and the alternatives move toward the left):

1. Technician utilization increases (from 35.27% to nearly 70%). Fewer technicians on watch means that each technician will be busier.

2. Availability decreases by 0.0005 – i.e., an increase in the average facility downtime of 4.4 hours per year.

3. The number of tasks waiting (maintenance backlog) increases by a factor of 10. This increase is a result of technicians not being available because they are busy on other tasks.

4. Average waiting time increases by a factor of 9, for the same reason as the increase in the maintenance backlog

5. The average outage time increases by a factor of 13 to approximately 32 hours. This is also related to the increase in maintenance backlog identified above.

Results 3 through 5 show the real cost of decreasing staffing: when there is an outage, it will take much longer to fix. This is a non-obvious result that emerges from an analysis using the analytical queuing equations modified to account for training and travel time described above. The increases in outage time are of particular concern from the perspective of capacity. Although these results do not necessarily mean that the highest impact equipment outages will not be promptly serviced, they do indicate that there will be an increased need for prioritization, meaning that lower maintenance priority equipment will be out for much longer times. Results 1 and 2 might be considered acceptable from the perspective of attempting to optimize resources, that is, increasing the level of activity of technicians and a relatively small decrease in availability are an unfortunate but necessary price to pay. However, when combined with the impact of waiting tasks, alternative approaches to allocation of resources would be considered. For example, a decrease of 20% of staffing has far more acceptable consequences.

CONCLUSION

With the increasing air traffic and growth of deployed FAA equipment, high equipment availability and low outage time is also becoming more important. While the use of simulation models and simple queuing models for assessing the impact of staffing on availability has been available for more than 5 decades, it has not been widely used because of the cost and complexity of implementation. The analytical methodology and SMART 4 tool presented in this paper overcome this obstacle. It is now possible for a non-expert to obtain rapid results and easily perform parametric studies on a variety of “what if” scenarios related to economics and capacity. The most significant benefit is that these results will now be available to analysts and decision makers. The net result will be more informed decisions that will be able to properly account for the impact of maintenance resources on capacity and overall NAS economics.

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